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ABSTRACT
Template-based analysis techniques are good candidates to robustly detect transient temporal graphic elements (e.g. event-related potential, k-complex, sleep spindles, vertex waves, spikes) in noisy and multi-sources electro-encephalographic signals. More specifically, we present the impact on a large dataset of a wavelet denoising to detect evoked potentials in a single-trial P300 speller. Using coiflets as a denoising process allows to obtain more stable accurracies for all subjects.

KEY WORDS
Event-related potential, wavelet denoising, support vector machines, brain-computer interface

1. Introduction

The observation of brain activity and its analysis with appropriate data analysis techniques allow to extract properties of underlying neural activity and to better understand high level functions. Several recording techniques exist providing different kinds of information at various scales. Some of them provide very local information such as multiunit activities (MUA) and local field potential (LFP) in one or several well-chosen cortical areas. Other ones provide global information about close regions such electrocorticography (ECoG) or the whole scalp such as electroencephalography (EEG). If surface electrodes allow to easily obtain brain imaging, it is more and more necessary to better investigate the neural code. Brain study needs to investigate and integrate, (i) in a single-trial, information (ii) spread in several cortical areas and (iii) available at different scales (MUA, LFP, ECoG, EEG).

2. Modeling and detection of transient events in cortical signals

2.1 Transient events in cortical signals

In cognitive experiments, typically the experimental task (one trial) is repeated many times and the resulting brain activity is averaged over trials. The main reason for this averaging is the low signal-to-noise ratio (SNR) in the single-trials and average increases the SNR dramatically. The average activity allows to extract easily event-related components, which are strongly related to cognitive processes in the brain. However, this averaging assumes that the brain responds to the external stimuli identically in all trials. However it has been shown in several previous studies that this assumption is not valid. Consequently, to improve the analysis we develop an algorithm to extract event-related components from single-trials.
Event-related potentials (ERP e.g. N200, P300, N400, P600...) and error-related potentials are not the only ones transient temporal graphic-elements used in brain analysis. Non-cognitive events such as spikes, sleep K-complex, epileptic spike-wave are other transient events. The information carried by all of them are highly useful to better understand mental state and brain activity.

2.2 Specific data analysis techniques

One major problem with transient events is how to be able to deal with the variability between trials. Thus, it is necessary to develop robust techniques based on stable features. Specific modeling techniques should be able to extract features investigating the time domain and the frequency domain. ERPs are short-time events with characteristic peaks at specific times. So it is useful to be able to extract features in time domain. In the time domain, template-based unsupervised models allows to extract graphic-elements. Both the average technique to obtain the templates and the distance, such as the point-to-point averaging, the cross-correlation distance and the dynamic time warping, used to match the signal with the templates are important, even when the signal has a strong distorted shape. Thus, template-based classifiers first estimate ERP templates by averaging in the time domain ERP responses, and then use the shorter distance between the current response and the ERP templates as a discriminate criterion.
This embedded approach is not the only one. Usually, it is useful to apply a denoising stage before the classification stage to detect the graphic-element.

3 Illustration: P300 single-trial detection for brain-computer interface

Brain-computer interface (BCI) system is a potentially powerful new communication and control option for those with severe motor disabilities [1]. A BCI system translates brain activity into commands for a computer or other devices (e.g. wheelchair, robotic arm). In other words, a BCI allows users to act on their real or virtual environment by using only brain activity.

One of the well-known and powerful BCI system is the P300 speller based on the non-invasive Electroencephalography (EEG) measuring from the subject's scalp [2]. The P300 speller [3] is one of the most well-known applications in Brain-Computer Interface (BCI). This application has potentially a strong impact for patients with motor disabilities given its high rate of accuracy and reasonable speed. Many improvements over the pioneering systems have been done and some comparisons exist [4]. This BCI system uses an oddball paradigm. Oddball paradigms are used in asynchronous BCIs to induce event-related potentials through visual or auditory stimulus. Subject pays attestation to specific stimuli that will induce ERPs when presented (figure 1); others are regarded as the background neural activities.

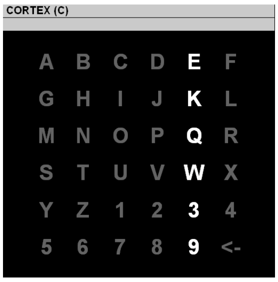

Figure 1: A 6x6 P300 speller. The application highlights in a random order columns and rows. The user looks at the desired letter. When the letter is highlighted, a P300 is generated. Detecting this specific transient event, it is possible to know which letter is requested.

One well-defined component of ERPs is the P300 component that is a positive deflection waveform observed around 300ms after the onset of the stimulus. Brain-Computer interfaces based on evoked potentials allow more commands than the ones based on mental tasks and do not need long human training. Almost everybody reacts on them and there are used by patients. Thus, the task of the P300 speller system is to recognize the ERP components from the noisy EEG background signal. It is found difficult to accomplish this target on the base of a single-trial because the magnitude of the EEG background activities is usually one-order larger than the one of the ERP components, that means the ERP components in single-trial recordings are almost covered by the background neural activities. Moreover, non-invasive electrodes produce a noisy signal because the skull dampens signals. Thus, ERP detection usually needs to average responses of repeated stimulations. Due to the averaging operation, the background EEG activities are reduced and the ERP components are enhanced and evident. From a practical point of view, an important issue is to reduce the number of repetitions, in order to obtain high communication bit-rates. The methodology has been improved but a gap still exists to enable single-trial recognition.
To validate our study, we used a large database obtained from first-time users of the P300 speller application implemented within the BCI2000 platform [2].

2.2 Database

The Neuroimaging Laboratory of Universidad Autónoma Metropolitana (Mexico) recorded 30 healthy subjects (18 Males/ 12 Females, age 21-25) controlling various conditions (sleep duration, drugs, etc). Each subject participated to 4 sessions with 15 sequences:
1) Three copy-spelling runs.
2) One copy-spelling run with feedback using a classifier trained on data from session one.
3) Three free-spelling runs (user-selected words, around 15 characters per subject).
4) Variable free-spelling runs with reduced number of sequences as indicated by bit-rate analysis.

10 channels (Fz, C3, Cz, C4, P3, Pz, P4, PO7, PO8, Oz) have been recorded at 256 sps using the g.tec gUSBamp EEG amplifier, a right ear reference and a right mastoid ground (figure 2). An 8th order bandpass filter, 0.1-60 Hz and a 60 Hz Notch have been used. The stimulus is highlighted for 62.5 ms with an inter-stimuli interval of 125 ms.

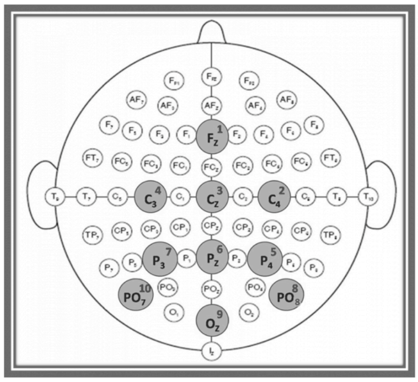

Figure 2: The 10 recorded EEG channels. We selected Fz, C3, Fz C4, P3, Pz and P4 to get the cognitive P300 potential and P07, P08 and OZ to also get some visual evoked potential components.

A complete description of the parameters used for the speller and the data are available in BCI2000 and Matlab formats on the database website: http://akimpech.izt.uam.mx/p300db.

We selected 16 subjects from the large dataset: 10 males and 6 females. All of them have similar characteristics (sleep duration, drugs, age, etc.).

4. Methods

Recent literature presents solutions for denoising ERP using specific wavelets [5, 6, 7]. We confused our attention on quadratic B-spline wavelets and coiflets at level 3 [8]. We want to test them on our large data set and compare their performance with standard algorithms, such linear dicriminant analysis and support vector machines, without denoising. We are especially interested by the single-trial detection which is the worst case because the response is very noisy if no averaging is performed.

4.1 Denoising by wavelet decomposition

The Wavelets Transform (WT) was developed as an alternative to the Short Fourier Transform to overcome the resolution problem [9]. WT is a windowing technique with variable regions size. The main idea is to represent a signal $x(t)$ in terms of displaced and shifted version of a mother wavelet $\Psi(t)$.

$$\Psi_{a,b}(t) = |a|^{-\frac{1}{2}}\Psi\left(\frac{t-b}{a}\right)$$

where a and b are the scale and translation parameters respectively.

The signal coefficients are obtained by the convolution of the original signal and the different version of the mother wavelet.

$$W_{\Psi}X(a,b) = \langle x(t)|\Psi_{a,b}(t)\rangle$$

The coefficients refer to the similarity in frequency content between the signal and the wavelet at the current scale.

Using the matlab, we extract at level 3 the coefficients of original signals using Coiflets and quadratic B-spline mother wavelets, due to their waveform similarity to the P300 and because they are recommended by the literature. These wavelets families are used to remove noise from the details coefficients belonging to the original signal. To do this we identified the components that contain the noise, and then reconstructing the signal using the approximation coefficients (A3) and the details coefficients without those noisy components. The noise is removed using a threshold, this involves discarding only the portion of the details that exceeds a certain limit (figure 3).

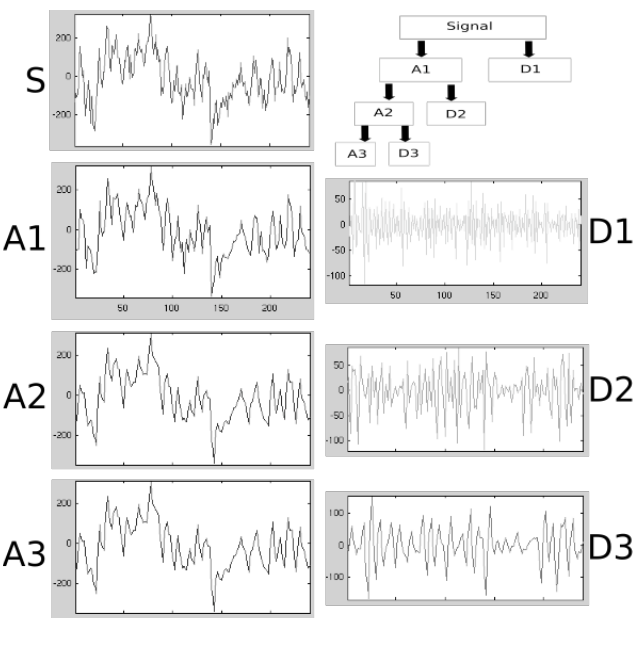

Figure 3: Signal decomposition illustration. The original signal S (top left) is decomposed at 3 levels (top right) obtaining the approximation (A1, A2 and A3) and details (D1,D2,D3) coefficients. The signal is reconstructed using A3 and the denoised versions of D1, D2 and D3.

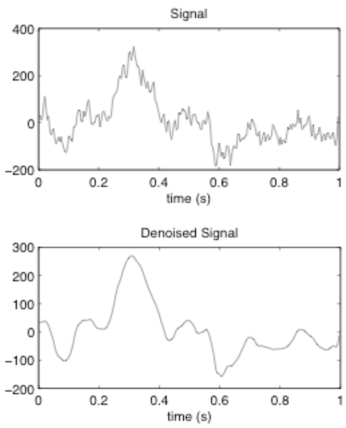

Figure 4: Effect of the denoising process on a P300 response. The original signal (on top) corresponds to the average of all targets signals for letter C in word CAT into the BCI competition IV, subject AA. The P300 is elicited around 0.3 second. The signal obtained after denoising using wavelets is shown at the bottom.

4.2 Classifiers

The Linear Discriminant Analysis (LDA) is the standard method used as a reference method for P300 detection in BCI. We used the stepwise version (SWLDA) implemented in BCI2000 to get results.

Support vector machines (SVM) are one of the most popular data mining techniques [10]. They are especially powerful for two-classes problem with a large number of variables. The complexity cost is dependent on the number of examples. So SVM are good candidates. We classified our binary dataset (target vs non-target) with linear kernel and a cost C = 1. A linear kernel is more robust than polynomial one for very noisy data with high variability.
We used libsvm, a library for Support Vector Machines by Chih-Chung Chang and Chih-Jen Lin and its simple interface for matlab [11].

For each subject, we used the data of session 1 to train the classifier (SWLDA or SVM) and session 3 to test it (free spell of 3 words).

5. Results

The standard SWLDA method obtains good results on averaged responses but it is not very efficient for single-trial detection (Figure 5).

SVM overtakes SWLDA (Figure 6). Using as a preprocessing wavelet denoising has some effects on the robusness of the classifier especially with the coiflets. The mean or median of the accuracies are similar with and without wavelet denoising. But a coiflet denoising more stable.

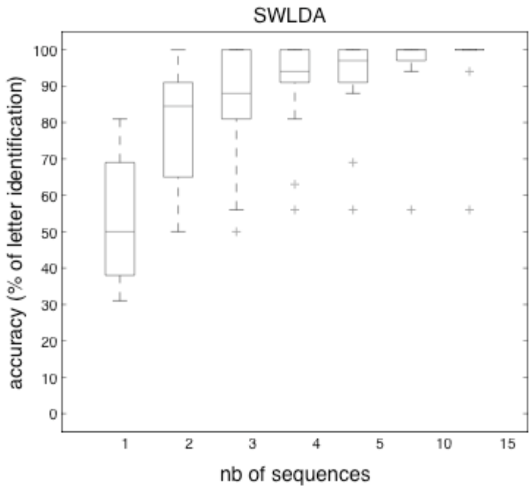

Figure 5: percentage of correct letters using stepwise linear discriminant analysis (SWLDA) via the P300GUI tool contribution for BCI2000. The box and whisker plots present a study of the 16 accuracies obtained using subject dependent classifiers. Each accuracy is based on the full test set i.e. on the three free-spelling runs (user-selected words, around 15 characters per subject).

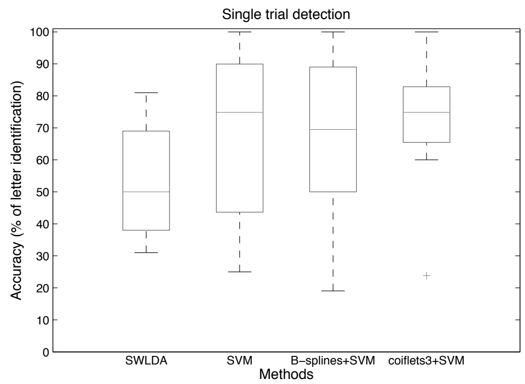

Figure 6: percentage of correct letters for the four competitive approaches on single-trial detection. Stepwise linear discriminant analysis (SWLDA) and support vector machines (SVM) without denoising plus SVM with two wavelet denoisings : B-spline wavelets and coiflets at level 3. The box and whisker plots present a study of the 16 accuracies obtained using subject dependent classifiers. Each accuracy is based on the full test set i.e. on the three free-spelling runs (user-selected words, around 15 characters per subject i.e. around 30 P300 responses and 150 non target responses).

6. Conclusion

In this work, we present the impact on a large database of specific wavelet families for denoising evoked potential from EEG background activities to easily detect them in a single-trial P300 Speller. These wavelet families are adapted to ERP waveform. Two different mother wavelets (B-Spline and Coiflets3) were used in the experiments according to there performance for ERP denoising in literature. Despite the fact that both mother wavelets “look similar” to the P300 wave, in a single-trial detection, the improvement of wavelet denoising is visible in terms of stability especially using Coiflets3.

Due we are working with a large dataset, it is difficult to get an algorithm that improves accuracy for all subjects, because of the differences between subjects brain activities and the noise effect in dataset. But SVM clearly overtakes SWLDA.

As a future work, we want to investigate a method to adapt the parameters involved in the denoising method to improve the performance according to the grand average P300 response of each subject.

Acknowledgements

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